



Sindall, K., Sturgis, P., Steele, F., Leckie, G., & French, R. (2019). A reassessment of socio-economic gradients in child cognitive development using Growth Mixture Models. *Longitudinal and Life Course Studies*, 10(3), 283-305.
<https://doi.org/10.1332/175795919X15628474680682>

Peer reviewed version

Link to published version (if available):
[10.1332/175795919X15628474680682](https://doi.org/10.1332/175795919X15628474680682)

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A reassessment of socio-economic gradients in child cognitive development using Growth Mixture Models

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NOVEMBER 2018

The authors gratefully acknowledge the support of the Economic and Social Research Council through the grant for the National Centre for Research Methods (NCRM; grant reference: RES-576-47-5001-01).

ABSTRACT

Recent social and educational policy debate in the UK has been strongly influenced by studies which have found children's cognitive developmental trajectories to be significantly affected by the socio-economic status of the households into which they were born. Most notably, using data from the 1970 British cohort study, Feinstein (2003) concluded that children from less advantaged backgrounds who scored high on cognitive tests at 22 months had been overtaken by age 5 by children from more advantaged origins, who had scored lower on the baseline test. However, questions have been raised about the methodological robustness of these studies, particularly the possibility that their key findings are, at least in part, an artefact of regression to the mean. In this paper, we assess Growth Mixture Models as an alternative approach for identifying and explaining cognitive developmental trajectories in children which is robust to regression to the mean. We apply this approach to longitudinal children's cognitive test score data from the Millennium Cohort Study. Our findings provide no support for the contention that more initially able children from disadvantaged backgrounds are 'over-taken' in cognitive development by less initially able children from more affluent backgrounds. We do, however, find that cognitive developmental trajectories are related to socio-economic status, such that initial class-based inequalities increase over time.

INTRODUCTION

Evidence of growing socio-economic inequalities in the UK, as in many other countries around the world (Picketty, 2014; Stiglitz, 2012; Wilkinson and Pickett, 2009), has led to a focus in policy research on the initial causes of such disparities and, in particular, on how economic inequality is reproduced from one generation to the next (Hout, 2015; Washbrook, Gregg and Propper, 2014). This body of research has demonstrated that disparities in cognitive development and educational attainment are evident at very early stages in the life course (Cunha et al., 2006; Goodman et al., 2009). Indeed, substantial social class gradients in cognitive test scores are found when children are as young as 18-24 months, which is perhaps the earliest stage at which it is feasible to administer valid and reliable measures of cognitive ability (Feinstein, 2015). Because cognitive ability and educational attainment are so key to later socio-economic outcomes (Heckman and Mosso, 2014), it is natural that policy-makers have drawn on this evidence to develop and justify policy interventions intended to improve intergenerational social mobility (Lupton 2015). For example, policies such as ‘Sure Start’ and ‘Pupil Premium’ in the UK, which aim to narrow attainment disparities across social class groups, provide additional resources to children from disadvantaged backgrounds at earlier points in the life course than has historically been the case. A key plank in the rationale underpinning this policy agenda is that interventions must be implemented as close as possible to the point in the developmental pathway at which socio-economic gradients begin to emerge.

Interventions which are targeted later in childhood, adolescence, or early adulthood may arrive too late, as intransigent inequalities and accumulation to existing advantage will already have set in.

Key to the debate over the timing of early years interventions have been studies which analyse longitudinal data on cohorts of young children to assess how cognitive developmental trajectories are related to socio-economic origins (Feinstein 2003; Schoon 2006; Blanden and Machin 2007; Parsons et al. 2011). While varying in the nature of their approach, these studies have generally used a methodology which assigns children to groups based on a cross-classification of cognitive test scores at the first point of measurement (generally taken at an early age, such as 24 months) and their parents’ socio-economic status (such as social class or income quantile) also at the first point of measurement. In its simplest form, this yields a four-category classification: a high ability high-socio-economic status (SES) group; a low ability-high SES group; a low ability-low SES group; and a high ability-low SES group. Cognitive ability scores are then compared

across the four groups at successive points of measurement. These studies, which we shall henceforth refer to as the ‘pre-assigned groups’ method, have consistently revealed two striking patterns. First, as noted above, children’s cognitive test scores exhibit stark socio-economic gradients by as early as 22 months. Second, and most importantly for our purposes here, the ‘high ability-low SES’ group tends to show a decline in test scores over subsequent measurement occasions relative to the test scores of the ‘low ability-high SES’ group. These countervailing trends result in a ‘cross-over’, whereby the able but disadvantaged group is ‘overtaken’ by the less able but more advantaged group by the age of approximately 7 (though the exact age at which the cross-over occurs is imprecisely measured and differs across studies). The cross-over effect is depicted in the well-known chart from Feinstein’s 2003 paper, which is reproduced in Figure 1 below.

FIGURE 1 HERE

While there is now little or no dispute regarding the emergence of socio-economic gradients in cognitive test scores early in childhood, scholars have questioned the validity of the methodology which produces the ‘cross-over’ effect (Read 2003; Tu and Law 2010; Jerrim and Vignoles 2013; Goldstein and French 2015; Dickerson and Popli 2016). These authors have pointed to a number of limitations in studies that have used the pre-assigned groups approach, including non-comparability of tests across measurement occasions, conflation of average and individual effects, the arbitrary nature of the group boundary definitions, and failure to account for non-random nonresponse and attrition (see Feinstein, 2015). The pre-assigned group method typically also discards the data of children who are in the middle of the ability and SES distributions, which potentially neglects other substantively interesting and policy-relevant developmental trajectories.

Most notably, however, criticism has focused on the potential for the cross-over effect to result as an artefact of regression to the mean (RTM), rather than any substantive differences between the groups. In assigning children to high or low ability groups on the basis of a single test score, some children will be misclassified as a result of measurement error. That is to say, some children will have achieved higher or lower test scores relative to their ‘true ability’ purely by chance. Thus, when the misclassified children are re-interviewed in subsequent waves, those in the high ability groups will tend to show a decline in test performance, while those in the low ability groups will tend to show an

improvement in test performance. In other words, there will be a regression to the mean effect.

Because test scores at the first point of measurement are already stratified by SES, regression to the mean should be most pronounced for the high ability-low SES and the low ability-high SES groups, because to have been allocated to the high and low ability groups, respectively, more children in these groups must have scored further from their 'true ability' compared to the other two groups. And this pattern is exactly what the Feinstein analysis reveals. Jerrim and Vignoles (2013) illustrate this theoretical expectation using simulated data, showing that the cross-over effect is obtained when the pre-assigned groups method is applied to simulated data generated from a population containing two groups with different time-invariant mean abilities.

These findings lead Jerrim and Vignoles to conclude that the pre-assigned groups method "can induce substantial bias in estimates of the educational achievement trajectories of different SES and ability groups and thus lead to the wrong conclusions being drawn from trends in the data" (2013, p904). They advocate instead the use of a measurement error correction procedure which they apply to data from the Millennium Cohort Study (MCS). Application of this procedure reveals the familiar social class gradient in cognitive test scores at the first measurement occasion in the MCS, but this gradient does not change appreciably over time (and does not, therefore, exhibit the cross-over effect).

However, the Jerrim and Vignoles procedure requires a restrictive assumption that a parallel test of cognitive ability is available at the first measurement wave. A parallel test is one which measures the same underlying construct but whose errors of measurement are uncorrelated with the alternative test score. As Goldstein and French (2015) note, these conditions are unlikely to be met very frequently in practice. And, from a practical perspective, even if it were feasible to develop parallel measures, their inclusion in study questionnaires which are already long and complex may well represent an unacceptable additional burden on cohort members, potentially leading to higher rates of attrition. Moreover, their procedure would not be applicable to important existing data sets such as the British Cohort Study and the National Child Development Study, for which only single measures of cognitive ability are available. It is important, therefore, that other methodological approaches are explored and evaluated which are also capable of overcoming the regression to the mean effect. In this paper, our objective is to assess the

utility of growth mixture models (GMMs) (Muthén, 2004) for this purpose. Note that GMMs should not be viewed as simply a measurement error correction procedure to the pre-assigned group method, rather GMMs are an altogether different and richer methodology, but one which nonetheless allows us to evaluate the same underlying substantive research question: how does socio-economic origin shape cognitive developmental trajectories?

The GMM extends the linear growth curve model (e.g. Goldstein, 2011; Singer and Willett, 2003; Steele, 2008) by identifying latent classes (subpopulations) of individuals who follow qualitatively distinct developmental trajectories, with different growth parameters (e.g., initial levels and growth rates) estimated for each of the latent classes. Latent class membership is identified by applying finite mixture models to individual variation in the growth parameters from the single latent growth curve model. In addition to providing a way of determining the number of different latent trajectory groups in a population and the shapes of their trajectories on the repeated outcome over time, GMMs allow trajectory group membership to be predicted by covariates (individual characteristics) via multinomial logistic regression. Put simply, a GMM can identify distinct cognitive developmental trajectory groups and then assess whether group membership is predicted by socio-economic status. Consequently, although the exact testable statistical hypotheses implied by the two approaches differ, the use of GMM allows us to address the same substantive questions as the pre-assigned groups method. Firstly, do children from different socio-economic origins follow qualitatively distinct cognitive developmental trajectories? And, secondly, are able but disadvantaged children ‘overtaken’ by their less able but more advantaged peers?

In line with the pre-assigned groups approach and Jerrim and Vignoles’ (2014) measurement error correction procedure for that approach, GMMs are not causal models. Nonetheless, the GMM framework does offer a number of attractive properties for studying the relationship between socio-economic status and cognitive development. First, it is not necessary to assign cohort members to high and low ability groups using a discrete threshold on the ability measure at the first point of observation. Instead, trajectory groups are based on test scores across all measurement occasions. For this reason, we should not anticipate that the trajectory groups thus defined will be subject to the regression to the mean effects experienced by the pre-assigned groups approach. Second, membership of the latent developmental trajectory groups is treated as

probabilistic rather than determined, which is preferable from both a conceptual and a measurement perspective. Third, because trajectory groups are not defined by specific socio-economic origin measures, it is possible to include multiple predictors of trajectory group membership. Finally, GMMs use all the available data. While the pre-assigned groups approach generally discards data from cohort members who are not defined as being in the high or low ability groups, the GMM framework uses all available observations. This means that we might expect to identify more than the four groups that the pre-assigned group approach is restricted to using GMM. It is also straightforward in the GMM framework to implement procedures which correct for nonresponse, attrition, and item missing data (Muthén et al., 2011).

This is not the first study to adopt GMMs in educational research; GMMs have been used to investigate issues such as pupil-teacher interactions and school drop-out (for example, see Brendgen et al., 2006, and Archambault et al., 2009, respectively) and the effects of birth weight (Espy et al., 2009), home learning environments (Rodriguez and Tamis-LeMonda, 2011), and competence in particular areas of learning (Aunola et al., 2004) on cognitive development. Studies that have considered the effect of SES on cognitive development have mostly included SES as a control for confounding rather than as a variable of direct substantive interest (see for example, Kaplan, 2009; Hodis et al., 2011; Hong and You, 2012; Spilt et al., 2012). An exception is Jordan et al. (2006) who found that children from low-income households performed consistently worse on cognitive tests compared to children from middle-income households and also developed at a slower rate over the course of their kindergarten year. A second exception is Pianta et al. (2008) who used GMMs to investigate the association between SES and cognitive ability scores of children aged 4 to 7 in the United States. Their analysis identified a group of ‘fast readers’ whose scores increased rapidly before decelerating and a group of ‘typical readers’ whose growth was steady and prolonged. Children from households defined as poor were less likely to be in the fast readers group than children who were not classified as poor.

Our paper develops and extends these existing studies in two ways. First, we apply GMMs to the MCS, a large representative sample of children from the UK. Second, we assess whether children from less economically advantaged backgrounds are ‘over-taken’ in their level of cognitive development by their more advantaged peers before

commencing secondary education. The remainder of the paper is structured as follows. In the next section, we present the specification of the GMM that we use to study socio-economic gradients in cognitive development. We then apply GMMs to data from the MCS and evaluate how the parameter estimates from our preferred model relate to the findings of existing studies. We conclude with an assessment of the substantive and methodological implications of our findings and of the suitability of GMMs for studying social class effects on cognitive development.

THE GROWTH MIXTURE MODEL

A GMM (Muthén, 2004; Muthén and Asparouhov, 2009; Vermunt, 2007) consists of a joint model for analysing repeated measures, conditional on individuals' latent classes, and for individuals' probabilities of belonging to each class. In the current context, the repeated measures are children's attainment scores across test occasions, while the classes represent subpopulations of children following qualitatively distinct developmental trajectories.

Let y_{ij} and t_{ij} denote a continuous attainment score and age at occasion i ($i = 1, \dots, n_j$) for child j ($j = 1, \dots, J$) and let C_j denote the latent class to which child j belongs, the values of which are indexed by k ($k = 1, \dots, K$). For the current application, preliminary analysis suggests that an appropriate GMM is where the attainment scores in each latent class are quadratic functions of time

$$y_{ij|C_j=k} = \beta_0^{[k]} + \beta_1^{[k]}t_{ij} + \beta_2^{[k]}t_{ij}^2 + u_{0j}^{[k]} + u_{1j}^{[k]}t_{ij} + e_{ij}^{[k]}. \quad (1)$$

The regression coefficients $\beta_0^{[k]}$, $\beta_1^{[k]}$ and $\beta_2^{[k]}$ measure the intercept, linear, and quadratic terms of the average quadratic attainment trajectory in latent class k , while the random-intercept and -slope effects $u_{0j}^{[k]}$ and $u_{1j}^{[k]}$ allow the intercept and linear components of this trajectory to vary across children. Thus, each child is allowed to follow their unique developmental trajectory. (For $n_j = 3$ occasions, an alternative but equivalent specification replaces the quadratic function by a binary indicator variable for each occasion.) The occasion-specific error or residual $e_{ij}^{[k]}$ allows the attainment scores to deviate from the perfectly quadratic child-specific trajectories. It is possible to include a random coefficient for the quadratic term, but at least four measurement occasions are

required for identification of all variances and covariances of the child random effects and the residual variance.ⁱ

The random effects in each latent class are assumed to be bivariate normally distributed with zero means and constant variances and covariance. The residuals in each class are assumed normally distributed with occasion-specific variances. Thus, in the most general specification, each class is characterised not only by its own average quadratic trajectory, but also by the extent to which children vary around their average trajectories, and in the degree to which the actual attainment scores vary about the child-specific trajectories.

We also estimate $\pi_j^{[k]}$, the posterior probability that child j belongs to each class, k , given their attainment scores, y_{1j}, y_{2j}, y_{3j} . Predictors of latent class membership can then be introduced by inclusion of covariates in a multinomial logistic regression for latent class membership. The model, expressed for simplicity in terms of a single child-level covariate, x_j , can be written as

$$\pi_j^{[k]} \equiv \Pr(C_j = k | x_j) = \frac{\exp(\alpha_0^{[k]} + \alpha_1^{[k]} x_j)}{\sum_{l=1}^K \exp(\alpha_0^{[l]} + \alpha_1^{[l]} x_j)}, \quad (2)$$

where $\alpha_0^{[k]}$ and $\alpha_1^{[k]}$ denote the intercept and slope regression coefficients and where the last class is set to be the reference category (i.e., $\alpha_0^{[K]} = \alpha_1^{[K]} = 0$). In the context of a GMM, a ‘cross-over’ effect pertains when we observe a class with a trajectory that has a lower predicted attainment score than another class at the first point of measurement but a higher score at the last point of measurement, such that the predicted trajectories cross over time.

In the analysis of the MCS data, we estimate equation (2) jointly with the growth model of equation (1) using full-information maximum likelihood estimation. This approach is commonly referred to as the one-step method (Muthén, 2004; Muthén and Asparouhov, 2009; Vermunt, 2007). In this specification, the covariates, such as socio-economic status, are not included in the growth curve model (1), and therefore do not have direct effects on the attainment scores, but are included in the class membership model (2). Nevertheless, by estimating both the growth curve and class membership model jointly,

SES and other covariates can have indirect effects on the estimated growth curves. Another widely used approach is the three-step method (Vermunt 2010; Asparouhov and Muthén, 2014) in which equations (1) and (2) are fitted in separate stages. However, a notable advantage of the one-step approach is that it is straightforward to accommodate missing achievement and covariate data under a missing at random (MAR) assumption. In a recent simulation study comparing the performance of the one-step and three-step methods, little difference was found between the two approaches (Asparouhov and Muthén, 2014). In our analyses we find that the inclusion of covariates in the joint model has little impact on the predicted trajectories, as shown in Figure A1 in the appendix.

Deciding on the number of classes is a key but difficult topic in growth mixture modelling. Reviews by Nylund et al. (2007), Tofighi & Enders (2008) and Yang (2006) suggest that the sample-size adjusted BIC (Schwarz, 1978) and LMR statistic (Lo, Mendell & Rubin, 2001) tend to perform well in extracting the correct number of classes. The adjusted BIC measures the goodness of fit, penalised for model complexity (i.e., number of model parameters and sample size) while the LMR is a modified version of a standard likelihood ratio test which recognises that LRT statistics which compare models with different numbers of classes have non-standard chi-squared distributions. The entropy statistic is also often reported in GMM analyses as a measure of the certainty with which individuals are assigned to classes (Celeux and Soromenho, 1996). Values near one indicate high certainty in classification and values near zero indicate low certainty. We fit all models in the Mplus software Version 7.2 (Muthén and Muthén, 1998-2013).

DATA AND MEASURES

The MCS is a longitudinal survey that began in 2000 and tracks the social, economic, and health status of a nationally representative random sample of children born between 2000 and 2001. The first survey wave had a response rate of 68% and an achieved sample size of 18,552. The following three waves of data collection were conducted when the children were 3, 5 and 7 years old, with response rates (conditional on being present in the first wave) of 78%, 79% and 72% and achieved sample sizes of 15,590, 15,246 and 13,857, respectively. Our analyses of the MCS data employed the provided design and attrition weight, which adjusts for oversampling of deprived areas in the first wave of the survey and non-response in the fourth wave. The survey design and

fieldwork outcomes and construction of weights are described in detail elsewhere (Hansen, 2012).

For our measures of cognitive ability, we use the scales administered and derived by the MCS team, which measure vocabulary and reading skills at ages 3, 5, and 7. At ages 3 and 5, the naming vocabulary subset of the British Ability Scale (BAS) was used. Children were shown brightly coloured pictures and asked to name the object in each picture. At age 7, a word reading test was administered, in which children were shown a series of words on a card and asked to read them aloud. The children were shown a maximum of 90 words, but if a child read 8 words in a block of 10 incorrectly the test was stopped (Hansen, 2012). To make comparisons between these tests over time, test scores were standardised to a mean of zero and standard deviation of one at each occasion. The test at age 7 was an assessment of slightly different language skills to those tested at age 3 and 5, but all tests are nonetheless indicative of a child's overall language ability. These tests have been used both by Jones and Schoon (2010) and Jerrim and Vignoles (2013) to compare changes in children's language skills over time. Descriptive statistics for these standardised test score variables, as well as the other variables used in the analysis (discussed below) can be found in Table A3 of the appendix.

As noted earlier, an advantage of the GMM is that we are not restricted to using only one measure of socio-economic status as a predictor of cognitive developmental trajectories. We therefore include three such measures in our models. The first is a measure of household income at wave 1. This is an equivalised income measure that adjusts household income for the number of adults and children in the household (Hansen, 2012). The second is a binary indicator of whether families were in receipt of one or more of the following benefit payments at wave 1: Job Seekers Allowance, Income Support, Work Families Tax Credit, or Disabled Person's Tax Credit. The third is the National Statistics Socio-Economic Classification (NS-SEC) of the current job held by the interviewed parent at wave 1, or, in the case of parents who were not in work, their most recent job (see Table A2 in the appendix for correlations between these three SES variables).

We also include the following covariates measuring aspects of family structure: the interviewed parent's marital status at wave 1; their (banded) age at child's birth; and

whether or not the interviewed parent had a longstanding illness, disability or infirmity at wave 1. Sex of cohort members is also included as a covariate in all models. Of course there may well be other covariates that would improve model fit, but the principal aim of this paper is to assess whether socio-economic status predicts developmental class membership, rather than to build a fully predictive model.

RESULTS

A compelling line of evidence in Jerrim and Vignoles' (2013) critique of Feinstein (2003) is that they found the crossing pattern using the pre-assigned groups method when using simulated data, even though no such pattern existed in the simulated population from which the sample data were drawn. We therefore began our analysis by applying GMM to simulated data to assess whether it successfully recovers features of the measurement model from which the data were generated. Data were simulated under the same assumptions as one of the designs considered by Jerrim and Vignoles (2013) where the latent classes were predicted by a single binary variable and trajectories were assumed constant over time. To preserve space, we present full details and results of the simulations in the supplementary materials and simply state our main finding here, namely that we found no evidence of any cross-over effect in the predicted trajectories for any of the scenarios considered using GMMs.

Our analyses of the MCS data used multiple sets of random starting values for the model parameters to increase confidence that global maximum likelihood estimates have been obtained (Muthén and Muthén, 1998-2013). We begin by examining the BIC, sample size adjusted BIC, and LMR *p*-values for unconditional models with an increasing number of latent classes to ascertain the optimal number of latent trajectory groups (Table 1).ⁱⁱ Log-likelihood values are also presented, as are entropy values as a measure of the separation of classes (although based on results from the analysis of simulated data shown in the supplementary materials, we note that entropy will in general be low when mean differences among classes are small or residual variance large). Muthén (2004) suggests the optimal number of groups should be determined by (i) statistical measures of model fit, (ii) substantive utility, and (iii) parsimony. Following this approach, we concluded that the five-group model is optimal (Table 1). In comparison to a four-group model the *p*-value of the LMR test becomes significant and the entropy slightly lower, but the two BIC statistics decrease substantially. With the addition of a 6th trajectory

group, the BIC and sample size adjusted BIC further decrease and entropy increases, but these differences are marginal. Moreover, the parameter estimates for the six-class model reveal the additional trajectory group to be a ‘splinter’ class, representing just 1% of children, which adds little in terms of substantive insight. We therefore prefer the slightly less well fitting but more parsimonious five-class model.

TABLE 1 HERE

Table 2 presents the posterior probability table for the unconditional five-class model. The labels for the 5 classes are taken from visual inspection of the average trajectories in each latent class. The posterior probability table is a cross-tabulation of the most likely (i.e., modal) class for each child by the mean posterior probability of belonging to each class. Thus, the mean probabilities reported in each row sum to 1. A model with clearly distinguished classes should have high values, approaching 1, along the main diagonal and low off-diagonal values, approaching 0 (Nagin 1999). Large off-diagonal values are indicative of indeterminacy between classes. In support of our decision to settle on a five-class model, the values on the diagonal are high, ranging from 0.72 to 0.85, and those on the off-diagonal are low and close to 0. Each class has been labelled according to its relative intercept and growth parameters, described in full below.

TABLE 2 HERE

Figure 2 shows predicted values for the latent trajectory groups for the conditional five-class modelⁱⁱⁱ. The parameter estimates for this model are presented in Table A1 in the Appendix. Note that we encountered irresolvable convergence problems for models allowing the covariance between the intercept and slope to be freely estimated within each class. We therefore constrained these covariances to be equal across classes. The plotted GMM solution bears strong similarities to the pattern in the Feinstein (2003) chart (reproduced in Figure 1). A group is identified which scores high on the baseline cognitive test and continues to achieve high scores over subsequent measurement occasions (‘high-stable’, 33% of children), while a second group is identified which initially scores low and continues to do so over the next two measurements, with some evidence of a decline in achievement between the second and third measurement occasions (‘low-stable’, 17% of children). There is also a group which achieves a high

score on the test at age 3 but whose performance on the test declines over time ('high-declining', 18% of children) and a group which initially scores low, but test scores then increase over successive waves ('low-improving', 28% of children). These four groups appear to replicate the pattern shown in the Feinstein chart, including the 'cross-over' effect between the high-declining and low-improving groups. Additionally, the GMM produces a small group of children ('very low-improving', 4% of observations) who achieve very low scores on the age 3 test but who then show a marked improvement over successive waves.

As we noted earlier, the emergence of additional classes of this kind is likely to result from analysing all the children in the sample, as opposed to only analysing those in the high and low ability groups at wave 1. To clarify, and as explained above, these 5 groups represent average attainment trajectories. The inclusion of child-specific random effects allows each child to have their own unique intercept and slope, following their own unique developmental trajectory. Moreover no individual child belongs to any one group with 100% certainty, but instead has a non-zero probability of belonging to each class (see Table 2).

FIGURE 2 HERE

Correlates of Latent Trajectory Group Membership

We turn next to an assessment of the correlates of group membership via multinomial logistic regression of group membership on the socio-economic status and household structure covariates. Table 3 presents the coefficient estimates and the associated standard errors for each covariate. Coefficients are the log odds of membership in the first group in the column header, relative to the 'low-improving' class, the reference group, for each unit increase in the covariate (additional contrasts are presented in Table A4). So, for example, 0.245 in the first cell of the second column (labelled 'high-stable vs. low-improving') is the expected change in the log-odds of being in the 'high-stable' group relative to the 'low-improving' group for each unit increase in equivalised household income, having adjusted for the other covariates.

Given the large number of contrasts in Table 3 and A4, we do not interpret all of them here. Rather, we focus our attention on the contrasts which pertain most directly to the question of whether declining and increasing performance on the tests is associated with socio-economic (dis)advantage. We also separately consider the correlates of the ‘very low-improving’ class, given that it was not anticipated to emerge *a priori*. In particular, we wish to exclude the possibility that this group arises as an artefact of measurement or analysis operations. For readers more comfortable interpreting model predictions than coefficients, we provide in the supplemental materials plots of the predicted probability of belonging to each latent class plotted against each covariate in turn, holding all other covariates at their sample mean values. These plots are a complement to the discussion of the regression coefficients below and lead to the same substantive conclusions.

TABLE 3 HERE

In Figure 2, the intercepts of the latent trajectories for all groups represent the mean scores for the groups at the first point of measurement. These intercepts are ordered by income, as would be expected from existing research. For example, the odds of membership in the highest scoring group (high-stable) relative to all other groups increases with parental income, social class, and (non) receipt of benefits. The only exception to this pattern is the contrast between the ‘low-improving’ and ‘high-declining’ groups, the two groups which cross over time (i.e. -0.008 is not significant in the first cell of the third column of Table 3). None of the three socio-economic variables show a significant difference in the odds of being in the low-improving group rather than the high-declining group. This is, of course, counter to the pattern reported in the literature using the pre-assigned groups approach. We also fitted these models using each socio-economic predictor in isolation to check whether the null results might have arisen due to multicollinearity, or some form of suppressor effect. However, none of the socio-economic variables significantly differentiates between the ‘low-improving’ and ‘high-declining’ groups when considered on its own either (see Table A2 for estimates of the correlations between the SES predictors). We therefore conclude that, while the GMM does detect two groups which exhibit a reversal in their achievement on the cognitive test scores between age 3 and age 7, there is no evidence to support the claim that these two groups differ in their level of socio-economic disadvantage.

Although socio-economic status does not differentiate between the two cross-over groups (the low-improving and high-declining groups), there is evidence from the model to suggest that socio-economic (dis)advantage is related to change in test performance over time. Figure 2 shows the high-stable and high-declining groups both have high intercepts, indicating approximately equivalent high performance in the age 3 baseline test. However, while the high-stable group maintains this high level of achievement over time, the performance of the high-declining group falls significantly and substantially over the two successive waves. The odds of membership in the high-stable group relative to the high-declining group are smaller for children from households with lower equivalised household income, in lower social class groups, and whose parents are in receipt of state benefits (see second column in Table A4).

Similarly, Figure 2 shows the low-improving and low-stable groups have small intercept coefficients, indicating a low score on the baseline test. Yet, while the low-stable group continues to perform poorly, the test scores of the children in the low-improving group increase significantly over time, on average. The pattern of covariate relationships for these two groups mirrors that found for the contrast between the high-stable and high-declining classes. The odds of membership in the low-improving group relative to the low-stable group increase with income and social class, though benefit receipt does not discriminate significantly between these two groups.

Returning to the research questions outlined in the introduction, we conclude that while there was no evidence of a ‘cross-over’ effect associated with SES, this does not imply that the cognitive developmental trajectories of this cohort during this period were unrelated to SES. Amongst initially low scoring children, those from more affluent backgrounds were more likely to experience a subsequent improvement on their test scores, while amongst initially high scoring children, those from less affluent backgrounds were significantly more likely to experience a decline in their test scores at ages 5 and 7.

We also find that gender is significantly related to group membership for all but one contrast (between the low-stable and very low-improving groups; see Table A4, column 7): girls appear disproportionately in the higher achieving latent classes. We therefore also fitted models separately for male and female cohort members and found essentially the same latent class solutions as presented here for the joint model. This suggests that

the latent class solution for the joint model is not driven by gender differences in cognitive development but, rather, that the gender mix varies across an essentially invariant pattern of latent trajectory groups.

Lastly, we turn to the very low-improving group, which is a small (only 4% of children; see Figure 2), but potentially substantively interesting group, which would not have been detected using the pre-assigned groups approach. The very low-improving group shows the lowest mean score on the age 3 test of all five groups, but this is followed by rapid improvement in test scores over the ensuing two waves. The odds of membership in the very low-improving group decrease with parental income and social class and for children whose parents are single and never married. This pattern of covariate associations is suggestive of the very low-improving trajectory group comprising children from more economically disadvantaged backgrounds but who have a stable family structure.

DISCUSSION

Public policy in the UK has moved in recent years toward making interventions at earlier points in the life course than has historically been the case. This reflects a growing recognition that quite substantial gradients in cognitive development and academic achievement are evident very early in childhood (Crawford, Macmillan & Vignoles, 2014; Cunha, Heckman & Lochner, 2006). Thus, the argument goes, if redistributive policy interventions are to have maximum impact on equalising important life outcomes, they need to be implemented at or before the point in the developmental pathway that socio-economic gradients begin to emerge.

A key plank in the evidence base supporting this early years policy framework has been provided by studies which track representative samples of children from birth, through childhood and into adolescence, such as the British Cohort Study and the Millennium Cohort Study. Researchers have analysed these and other datasets to show not only that large differences in cognitive test scores are evident at early points in the life course, but also that children from different socio-economic backgrounds appear to pursue quite different cognitive developmental trajectories. Of particular significance has been the finding that initially less able children from more affluent backgrounds ‘overtake’ initially more able children from less advantaged families between the ages of 5 and 7 years (Feinstein 2003; Schoon 2006; Blanden and Machin 2007; Parsons et al. 2011). This

stylised fact has been cited by key political actors and referenced in a number of important UK government reports in support of early intervention policies (Lupton, 2015).

However, scholars have questioned the validity of the methodology underpinning this key conclusion, arguing that the ‘cross-over’ effect is a statistical artefact caused by regression to the mean (Tu and Law 2010; Jerrim and Vignoles 2013). Yet, while these studies have convincingly demonstrated that the conventional approach to analysing this kind of data - what we have termed the ‘pre-assigned groups’ approach - is likely to be subject to regression to the mean effects, we cannot conclude from this evidence alone that the cross-over effect does not happen, nor that socio-economic status does not affect cognitive development in other, perhaps more subtle ways. As Tu and Law note in their methodological critique of Feinstein (2003) and Blanden and Machin (2007), “it is not the case that the conclusions from studies whose data analyses suffer regression to the mean are always invalid” (Tu and Law, 2009, p1249). It is essential, then, that alternative methodological approaches are developed to address this key policy question, not least because, the measurement error correction method proposed by Jerrim and Vignoles (2013) is quite restrictive in its data requirements.

The GMM framework, we have argued, offers a number of potential advantages over these approaches to the study of social class gradients in cognitive development. GMMs easily incorporate information from multiple waves. Where the number of time points is greater than three, it is possible to introduce quadratic and higher order polynomial growth functions or splines, which vary across latent trajectory groups allowing more flexible approaches to capturing individual heterogeneity in developmental change. GMMs are also able to deal with unit and item missing data, an inevitable feature of cohort studies. In the analyses presented here, we used a full information maximum likelihood estimator (Arbuckle 1996), which is consistent and efficient assuming missing data to be missing at random (MAR) conditional on the observed data. Other approaches for dealing with missing data, such as multiple imputation, and nonresponse weighting can also be implemented in software for estimating GMMs. Most importantly with regard to regression to the mean, GMMs do not require trajectory groups to be defined at the first observation by placing arbitrary thresholds on the test score. Instead,

the groups are derived as a function of individual change across all measurement occasions.

In line with Jerrim and Vignoles (2013), we use the MCS, which first tested children at the age of 3, while Feinstein (2003) used the 1970 BCS which includes test scores from the age of 22 months. While GMM would remain robust to measurement error in comparison to the pre-assigned groups method, our substantive results may well differ if the age children were first tested was different. Nevertheless, in our analysis of the MCS data, the preferred GMM produced a solution very similar in structure to the Feinstein (2003) chart. Thus, the model yielded a group with a high initial test score which was maintained over successive waves, a group with a low initial test score which did not improve over subsequent waves, a group which started with a low test score but then improved over time, and a group which scored high on the baseline test but whose performance then declined. The latter two groups exhibited the ‘cross-over’ pattern that has come to attract so much attention in both policy and academic debate. Additionally, the GMM produced a small fifth latent trajectory group, characterised by a very low initial test score followed by substantial and sustained improvement over the subsequent two waves.

However, while the GMM produced two large groups which crossed in their trajectories, we found no evidence that membership of the rising versus the declining group was related to socio-economic status, whether measured using household income, social class, or receipt of state benefits. The GMM did, though, provide evidence in support of the contention that socio-economic status is associated with widening gradients in cognitive test scores at this point in the life course. Our analyses showed that the group of children who start poorly but improve over time are more likely to be in higher socio-economic groups than those who achieve low initial scores and do not improve. Conversely, we found that children who start with high initial scores but subsequently decline are more likely to be from less socio-economically advantaged backgrounds compared to the group that achieve high initial test scores and continue to perform well in subsequent tests.

Thus, while the GMMs fitted to MCS data provide no evidence in support of the claim that “by the age of five, bright children from poorer backgrounds have been overtaken

by less bright children from richer ones” (Nick Clegg, 2011), neither do they accord with Jerrim and Vignoles’ conclusion that, “although family background has a major influence on the child’s earliest level of cognitive development, it does not have a strengthening effect that would cause SES gaps in children’s cognitive achievement to widen further beyond the age of 3 years” (2013, p905). In fact, our results are closer substantively to those of Goldstein and French (2015) who, using the same MCS data but employing linear growth curve models, also find evidence of growing disparities in cognitive performance as a function of household income.

While the visually powerful image of bright working-class children being overtaken by their less able but more affluent peers appears to be incorrectly characterised as a general phenomenon, at least in these data, our findings suggest that the critique of the evidence on which this was based may itself have been something of an over-correction. The application of GMMs leads us to conclude that this method has much to recommend it in this substantive context and that socio-economic status is related to change in as well as to levels of cognitive ability at this early stage of the life cycle. From a policy perspective, this suggests that there are likely benefits from early intervention, but GMMs are not causal models, so any such interventions should be properly trialled and evaluated.

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ⁱ For $n_j = 3$ occasions per child, as in our application to the MCS data, there are 6 degrees of freedom for modelling the within-child association structure. A growth model with child-level random effects for the intercept, slope and quadratic terms and an occasion-specific residual has $6 + 1 = 7$ parameters, and is therefore not identified with only 3 occasions.

ⁱⁱ The unconditional model does not include predictors of latent class membership.

ⁱⁱⁱ This is the conditional model, which includes predictors for latent class membership. However, the inclusion of predictors of class membership has little impact on the plotted trajectories (the trajectories for the 5 class model fitted without covariates can be found in Figure A1 of the appendix).

TABLES AND FIGURES

Table 1. Model fit statistics and entropy for unconditional GMMs with different numbers of latent classes fitted to MCS data

Number of classes	Log- Likelihood	Free Parameters	BIC	Sample Size Adjusted BIC	LMR p-value	Entropy
2	-50756	15	101655	101608	<.001	0.681
3	-50504	21	101208	101141	<.001	0.742
4	-50426	27	101110	101024	0.011	0.701
5	-50187	33	100690	100585	<.001	0.666
6	-50106	39	100583	100459	<.001	0.688

Table 2. Average class membership probabilities by most likely classes for unconditional 5-class model

		Average latent class membership probabilities				
Groups		High-stable	High-declining	Low-improving	Low-stable	Very low-improving
Most likely group	High-stable	<i>0.829</i>	0.093	0.073	0.003	0.001
	High-declining	0.132	<i>0.721</i>	0.043	0.103	0.002
	Low-improving	0.132	0.028	<i>0.752</i>	0.066	0.023
	Low-stable	0.005	0.106	0.084	<i>0.774</i>	0.031
	Very low-improving	0.002	0.004	0.066	0.074	<i>0.854</i>

Table 3. Parameter estimates from five-class multinomial logistic model for trajectory group membership. Estimated coefficients are covariate effects on contrasts between the ‘high-stable’, ‘high-declining’, ‘low-stable’ and ‘very low-improving’ groups versus the reference group ‘low-improving’.

	High-stable vs. low-improving	High-declining vs. low- improving	Low-stable vs. low-improving	Very low- improving vs. low-improving
Standardised Income	0.245* (0.052)	-0.008 (0.066)	-0.632* (0.116)	-1.337* (0.261)
Benefit Payments (Ref: No)				
Yes	-0.368* (0.105)	-0.065 (0.123)	0.135 (0.118)	-0.085 (0.205)
NS-SEC (Ref: Managerial/prof)				
Intermediate	-0.416* (0.106)	-0.076 (0.137)	0.053 (0.173)	-0.057 (0.332)
Self Employed	-0.132 (0.196)	0.221 (0.234)	0.619* (0.266)	1.076* (0.402)
Technical	-0.626* (0.193)	0.294 (0.193)	0.511* (0.219)	0.671 (0.375)
Routine	-0.819* (0.120)	-0.05 (0.136)	0.727* (0.155)	0.850* (0.285)
Marital Status (Ref: single)				
Married	-0.121 (0.095)	-0.164 (0.111)	-0.190 (0.112)	1.513* (0.313)
Divorced/Separated	0.059 (0.178)	-0.033 (0.197)	0.203 (0.183)	1.093* (0.383)
Widowed	0.811 (0.940)	0.482 (1.051)	-0.832 (1.803)	3.748* (0.978)
Parent Long Term Illness (Ref: No)				
Yes	0.003 (0.091)	-0.059 (0.111)	0.074 (0.493)	-0.151 (0.188)
Parent’s Age at Birth (Ref: Under 20)				
20-39	0.228 (0.244)	-0.105 (0.202)	-0.166 (0.175)	-0.307 (0.390)
40+	0.262 (0.333)	0.071 (0.337)	-0.232 (0.364)	-0.153 (0.664)
Child’s Gender (Ref: Male)				
Female	0.574* (0.077)	0.277* (0.122)	-0.472* (0.097)	-0.503* (0.163)

*p<=0.05; Standard errors in parentheses

Additional group contrasts are presented in Table A4

Figure 1. Reproduction of Figure 2 of Feinstein (2003) showing average percentile rank of test scores at age 22, 42, 60 and 120 months, by SES of parents and whether in the top or bottom test score quartile (Q) at age 22 months (22m).

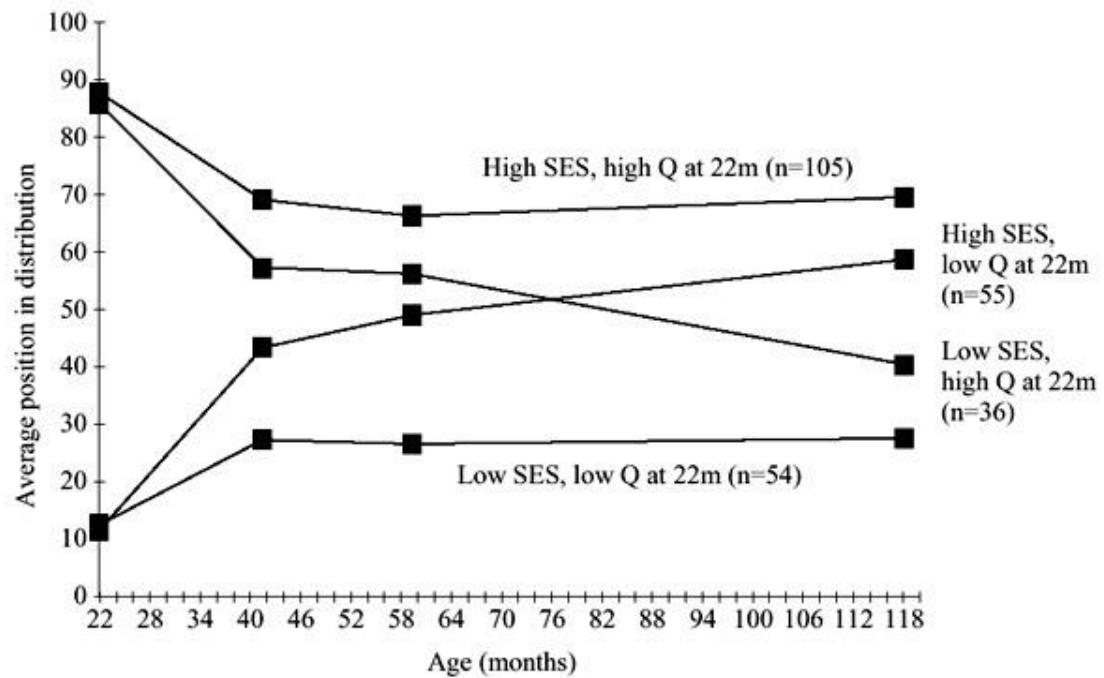
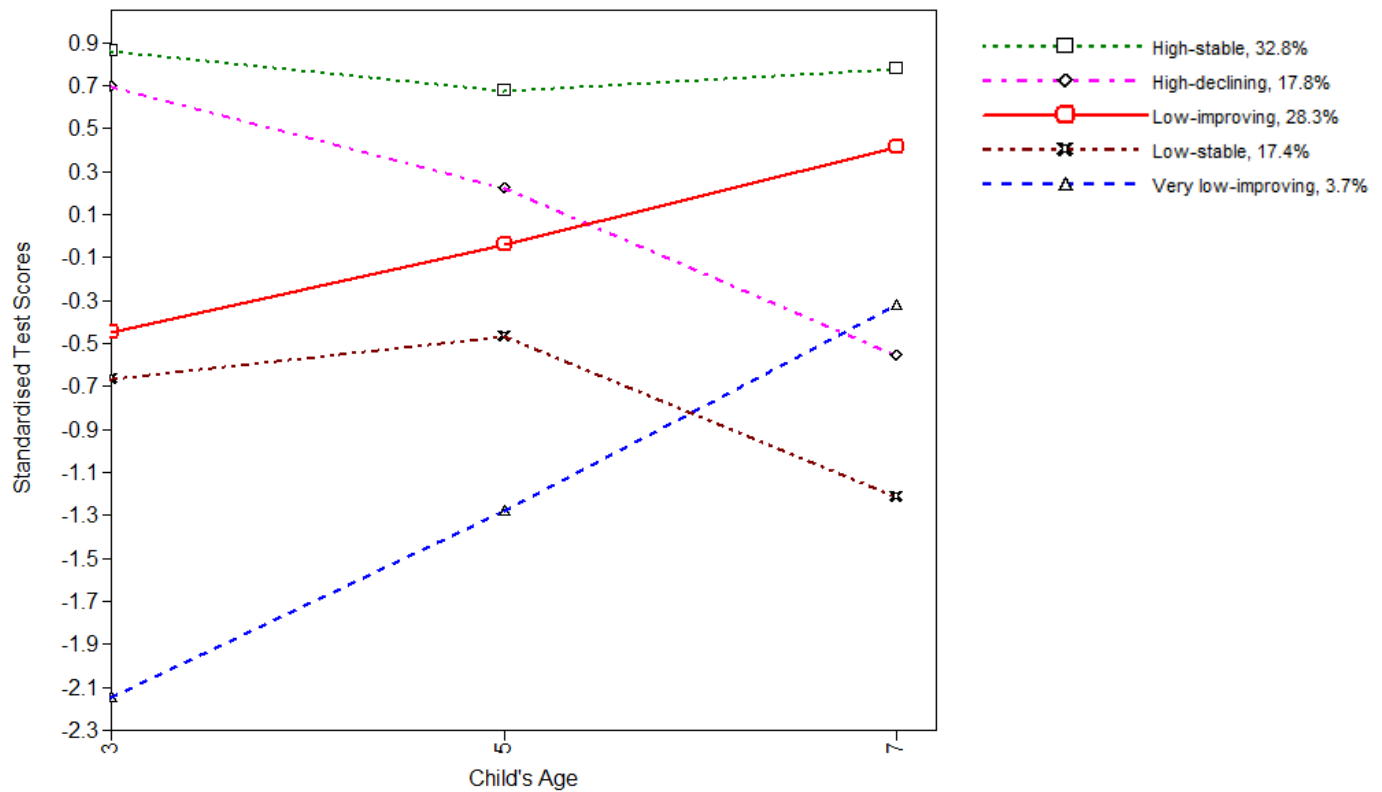


Figure 2. Predicted trajectories and latent group membership probabilities from conditional 5-class GMM model fitted to MCS data



Appendix

Figure A1. Predicted trajectories and latent group membership probabilities from unconditional 5-class GMM model fitted to MCS data

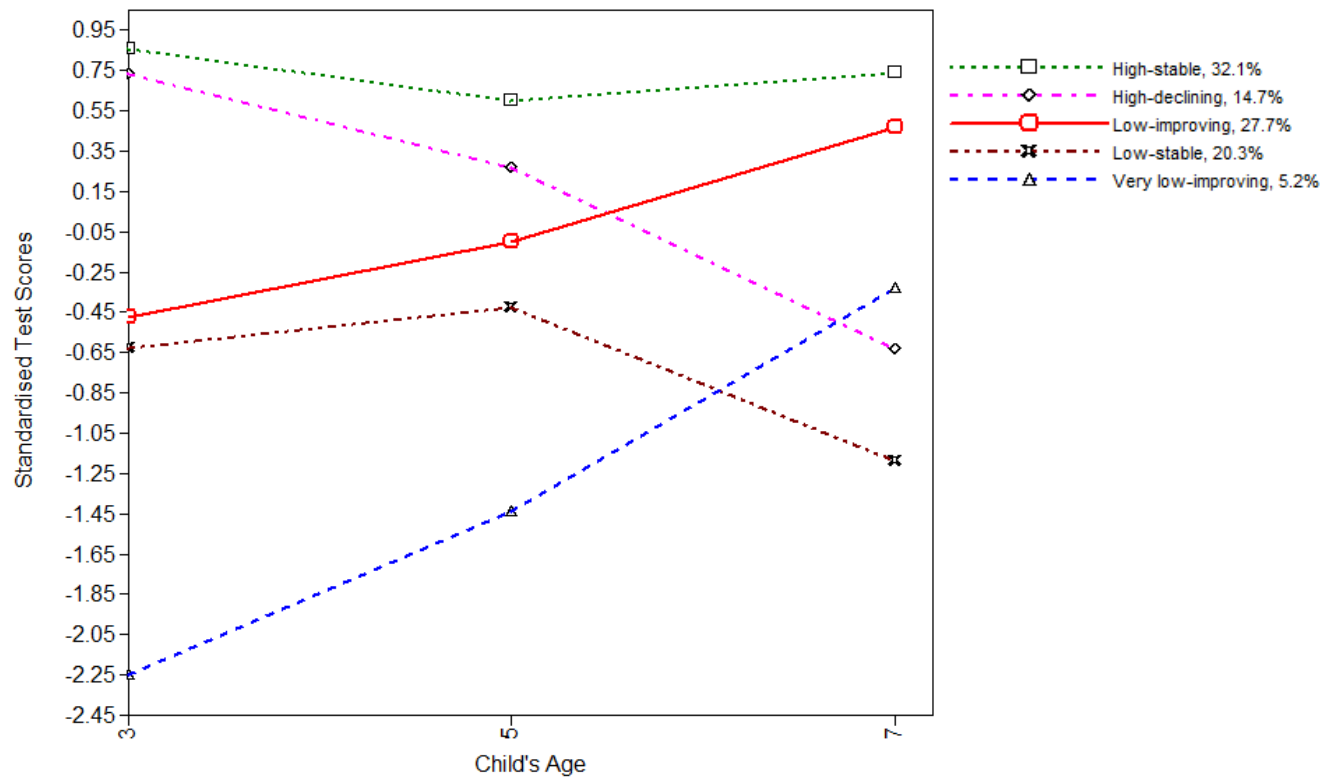


Table A1. Estimates of growth parameter from 5-class conditional GMM fitted to MCS data

Group	Intercept	S.E	Slope	S.E	Quadratic	S.E	Intercept-Slope Covariance	S.E	Estimated posterior %
High-stable	0.857*	0.019	-0.325*	0.046	0.141*	0.021	-0.070*	0.011	33
High-declining	0.689*	0.036	-0.313*	0.101	-0.156*	0.071	-0.070*	0.011	18
Low-improving	-0.451*	0.019	0.391*	0.052	0.019	0.029	-0.070*	0.011	28
Low-stable	-0.674*	0.032	0.675*	0.063	-0.474*	0.033	-0.070*	0.011	17
Very low-improving	-2.189*	0.086	0.870*	0.212	0.023	0.099	-0.070*	0.011	4

*p<.05

Table A2. Correlations between socio-economic status variables

	Standardised Income	Benefit Payments	NS-SEC: Intermediate	NS-SEC: Self- employed	NS-SEC: Technical
Standardised Income					
Benefit Payments	-.57				
NS-SEC: Intermediate	.04	-.08			
NS-SEC: Self employed	.03	-.07	-.10		
NS-SEC: Technical	-.07	.04	-.12	-.05	
NS-SEC: Routine	-.44	.37	-.41	-.17	-.22

Table A3. Descriptive statistics

	N	Mean	Standard deviation	Min	Max
Standardised Age 3 Reading Score	14759	0.00	1.00	-3.45	2.78
Standardised Age 5 Reading Score	15128	0.00	1.00	-4.14	3.11
Standardised Age 7 Reading Score	13553	0.00	1.00	-2.28	2.37
Standardised Income	18535	0.00	1.00	-1.40	5.07
	N	%			
Benefit Payments:					
No	10666	57.1			
Yes	8013	42.9			
NS-SEC:					
Managerial/prof	4895	29.6			
Intermediate	3132	19.0			
Self Employed	656	4.0			
Technical	1007	6.1			
Routine	6840	41.4			
Marital Status:					
Single	6241	33.3			
Married	11158	59.6			
Divorced/Separated	1281	6.8			
Widowed	40	0.2			
Parent Long Term Illness:					
No	14769	78.9			
Yes	3943	21.1			
Parent's Age at Birth:					
Under 20	1601	8.5			
20-39	16729	89.3			
40+	407	2.2			
Child's Gender:					
Male	9609	51.3			
Female	9131	48.7			

Table A4. Parameter estimates from 5-class multinomial logistic model for trajectory group membership. Estimated coefficients are covariate effects on contrasts between groups ‘high-declining’ and ‘low-stable’ and the reference group ‘high-stable’, between the group ‘low-stable’ and the reference group ‘high-declining’, and between groups ‘high-stable’, ‘high-declining’ and ‘low-stable’ and the reference group ‘very low-improving’.

	High-declining v high-stable	Low-stable v high-stable	High-declining v low-stable	High-stable v very low- improving	High-declining v very low- improving	Low-stable v very low- improving
Standardised Income	-0.253* (0.058)	-0.878* (0.110)	0.625* (0.118)	1.583* (0.260)	1.329* (0.261)	0.705* (0.281)
Benefit Payments (Ref: No)						
Yes	0.303* (0.133)	0.502* (0.116)	-1.199 (0.145)	-0.283 (0.205)	0.020 (0.214)	0.220 (0.212)
NS-SEC (Ref: Managerial/prof)						
Intermediate	0.340* (0.149)	0.469* (0.159)	-0.129 (0.205)	-0.359 (0.328)	-0.019 (0.339)	0.110 (0.359)
Self Employed	0.353 (0.242)	0.750* (0.244)	-0.397 (0.305)	-1.208* (0.396)	-0.855* (0.414)	-0.458 (0.433)
Technical	0.921* (0.224)	1.138* (0.215)	-0.217 (0.243)	-1.297* (0.376)	-0.377 (0.377)	-0.160 (0.395)
Routine	0.769* (0.147)	1.546* (0.148)	-0.777* (0.182)	-1.669* (0.285)	-0.900* (0.290)	-0.123 (0.308)
Marital Status (Ref: Single)						
Married	-0.043 (0.118)	-0.069 (0.109)	0.027 (0.133)	-1.634* (0.309)	-1.677* (0.309)	-1.704* (0.316)
Divorced/Separated	-0.092 (0.207)	0.144 (0.412)	-0.235 (0.210)	-1.034* (0.380)	-1.126* (0.384)	-0.890* (0.378)
Widowed	-0.329 (0.883)	-1.643 (1.633)	1.314 (1.828)	-2.937* (0.894)	-3.266* (1.025)	-4.580* (1.895)
Parent Long Term Illness (Ref: No)						
Yes	-0.062 (0.118)	0.072 (0.106)	-0.134 (0.131)	0.154 (0.187)	0.092 (0.194)	0.225 (0.195)
Parent’s Age at Birth (Ref: Under 20)						
20-39	-0.333 (0.276)	-0.394 (0.221)	0.062 (0.203)	0.535 (0.409)	0.202 (0.387)	0.140 (0.384)
40+	-0.192 (0.388)	-0.494 (0.375)	0.302 (0.408)	0.415 (0.675)	0.223 (0.667)	-0.079 (0.682)
Child’s Gender (Ref: Male)						
Female	-0.296* (0.129)	-1.046* (0.096)	0.750* (0.136)	1.077* (0.162)	0.781* (0.184)	0.031 (0.173)

*p<=0.05; Standard errors in parentheses

Additional group contrasts are presented in Table 3